ASEE 2022 ANNUAL CONFERENCE
Excellence Through Diversity
MINNEAPOLIS, MINNESOTA, JUNE 26TH-29TH, 2022 ASEE

Paper ID #37789

Impact of Late Policies on Submission Behavior and Grades in Computer Programming

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Abstract

This paper investigates the effect of four different late policies on submission behavior and grades in an introductory Computer Programming Lab class taught in the Java programming language at Loyola Marymount University, a primarily undergraduate university. To ensure grading consistency across sections, every student was randomly assigned two labs per late policy, for a total of eight labs completed over the course of the semester. The four late policies consisted of: 1) No penalty for late submissions, 2) Early incentive (one extra credit point awarded per day early the lab was submitted, up to three points max), 3) Late penalty (25% off within 24 hours of the deadline, 50% off for 24-48 hours late, 75% off for 48-72 hours late, and zero credit after 72 hours), and 4) Combined (early incentive combined with a late penalty). For our quantitative and qualitative study, we measured, per policy (for a total of 248 submitted labs), the average lab grade and the average number of days the labs were submitted early or late, as well as the average student rankings (from 1 to 4, where 1 was their favorite and 4 their least favorite policy). We found that while students rated Early Incentive the highest, the policy with the highest lab grades and submitted the earliest on average was the Combined early incentive with a late penalty. The worst grades were for No penalty, which may suggest a late penalty is necessary to keep students on track.

1 Introduction

Deadlines are inescapable in daily adult life, and college can be regarded as a key time to learn how to manage and meet them. Late policies are standard fare in most courses, to ensure that students (and faculty!) don't fall behind. *Motivating* timely submissions can be done via incentive, disincentive, or both—typically, an instructor chooses a policy that works for them and stays with that throughout a course.

However, courses vary widely in terms of subject matter, expected workload, type of deliverable, and more. Comparing late policies across courses involves a significant variable: the course itself. As such, we set out to study the impact of late policies on submission behavior for a particular course by rotating among them within the same offering. The premise here was that by holding the students, instructors, and content constant, it may be possible to then attribute outcomes and behavior more precisely to the late policy in use at the time.

The course studied here, entitled Computer Programming Lab, seeks to build upon an initial Introduction to Computer Science course with a sequence of medium-sized problems or "labs." The course is taught apprenticeship-style: after the instructor introduces the programming problem, the students then set out to complete the program for several sessions *during* class. During these sessions, the instructor makes the rounds to answer questions, provide some guidance, and make suggestions. This approach is chosen so that instructors can interact with a student *while* programming is taking place rather than look solely at the finished/submitted product, with the ability to provide feedback interactively and on the spot.[1,2] Deliverables for each program include the code itself along with a lab report including specific uses of the program, cases of interest, and introspection on time spent and level of difficulty.

The coronavirus pandemic affected this study as originally envisioned by forcing the course online. Instructor interaction was conducted over Zoom, whether in a shared session or in one-on-one breakout rooms as a substitute for "making the rounds" physically. Thus, a follow-up experiment on a similar course but in an in-person setting may be called for to determine how this unexpected remote aspect might have affected submission behavior.

The variable late policy was implemented with an eye toward ensuring that students did not feel unfairly advantaged nor disadvantaged by the rotations, and so all students had a turn with each variation. First, the policy was implemented as a course-wide, syllabus-level policy—it was done independent of the research that was taking place. Students were then asked to opt in to whether their submission behavior may be included in this study. Late policy groupings were made so that every policy was represented in every lab assignment. The variations were as follows:

- *No policy*—Lab will be accepted for credit after the deadline.
- *Early incentive*—One extra credit point for each day early lab is submitted, up to 3 days. Lab will be accepted for credit after the deadline.
- *Late penalty*—Lab will be accepted for partial credit after the deadline up to 3 days late. Late submissions will be graded as follows:
  - Within 24 hours of the deadline, 75% credit
  - 24 to 48 hours after the deadline, 50% credit
  - 48 to 72 hours after the deadline, 25% credit
  - After 72 hours, zero credit
- *Early incentive + Late penalty*—-One extra credit point for each day early lab is submitted, up to 3 days. Lab will be accepted for partial credit after the deadline up to 3 days late. Late submissions will be graded as follows:
  - Within 24 hours of the deadline, 75% credit
  - 24 to 48 hours after the deadline, 50% credit
  - 48 to 72 hours after the deadline, 25% credit
  - After 72 hours, zero credit

By holding the specific course offering, instructors, and pool of students constant, it is hoped that this work sufficiently distills differences in submission behavior primarily based on the incentive or disincentive that is in place for submitting early, on time, or late. The specific course involved has also been described in case the course content and workload may be seen as affecting the submission behavior.

2 Related Work

2.1 Flexible Late Policies

Prior work compared student and faculty perceptions of late penalties, as well as investigated several different deadlines in STEM courses. It was found that while students perceive deadlines as strict, faculty believe they are more flexible.[3] In computing courses, there were benefits to setting clear deadlines with increasing late penalty proportional to lateness, offering bonus points for on-time submissions, and allowing assignment re-submissions in order to emphasize achievement and build confidence.[4] While this work is similar to ours, we also perform a quantitative analysis of four specific late policies' effects on grades and submission behavior. Another related study examines the effect of four different late policies on submission behavior in chemistry courses,[5] showing that "there does not appear to be any benefit to accepting late work in cases where a sizeable penalty is also applied. For teachers looking to maximize the amount of work turned in, application of a short grace period seems to be the best route." We also examine four different late policies, although we include two with an early incentive (i.e., bonus points for early submission) and apply it to an online computer programming course. In addition to studying submission behavior, we also survey the students and analyze the effect on their grades.

A recent case study situates flexibility as a necessary response to the mental, physical, and relational health disturbances students face due to the coronavirus pandemic.[6] For Thierauf, flexibility was the difference between several students completing the course or not. Our student participants, being in the Spring 2021 semester, were also navigating challenges of online learning and strains beyond their academic lives. We handled exceptional circumstances and emergencies on a case–by–case basis. Over a decade before the pandemic, Patton also concluded flexibility led to more positive results.[7]

Richter describes how significantly culture influences perception of deadlines and approach to time management.[8] Some cultures have a monochronic sense of time which emphasizes schedules, segmentation, and promptness. Alternatively, a polichronic culture relates to time in a non-linear fashion and is more concerned with the people involved and the completion of a project, as opposed to the order of events sticking to a certain schedule. As such, the degree to which a late policy is flexible may be well-suited to some students' way of relating to time and go against the grain for others, causing frustration. Their respective lenses will also determine students' perception of how flexible the policy is if consequences of not meeting deadlines are not made clear. Varied cultural preferences and therefore varied experiences of a learning environment implies there being benefit to flexible, individualized practices.

An alternative approach to late policy variation is the idea of *late days*—with this approach, a student may choose a subset of assignments for which lateness is not penalized.[9,10] The approach used in our study is similar to having "preassigned" late days—i.e., the student knows in advance which assignments have submission time incentives or penalties. We acknowledge, however, that a primary feature of the late-days approach is the ability to *choose* such days, and thus student agency as a variable would be worth considering for future work.

2.2 Procrastination

Quite a few studies have investigated the effect of student procrastination on grades, as well as the impact of late policies on submission behavior. Prior work showed that submission behavior is a reliable predictor for identifying "at-risk" students in computer science.[11] 70% of college students identify as procrastinators.[12] Procrastinating on assignments has been shown to lead to poor goal achievement[13] and poor quality of work due to time pressure.[14] In addition, there has been a shift toward online learning during to the COVID-19 pandemic, resulting in even higher rates of procrastination due to the increase in self-regulation required of students during remote instruction.[15] Perhaps cogent to the physical and mental health issues generated by the pandemic, procrastination has been shown not only to lead to lower grades and performance but also produces increased stress and illness late in a term.[16] Interestingly, that same study reports *decreased* stress and illness earlier on. Our study, with its varying policies implemented from the beginning of the course term, may help shed light on this difference.

While environmental factors impact the submission behavior of low-procrastinating students, "procrastination-friendly" environments can lead to an increase in procrastination for medium-procrastination students, which is the majority of students.[17] An early MIT study on self-control and deadlines showed that people are willing to self-impose deadlines, but that they are not as effective in improving task performance as externally-set deadlines.[18] These studies indicate that late policies help externally regulate students in order to maximize their performance. Studies on procrastination have been conducted under a wide array of contexts;[19] we situate this work not only within the context of computer science education, but for a specific course that is conducted in a specific way. Due dates have also been shown to be beneficial in online formats[20] so although the results reported may affect the *degree* of impact, we do not expect a directional shift by being online vs. in-person.

2.3 Timely Feedback

Some work has suggested that the availability of immediate feedback is a factor in timely submission behavior.[21] The course that was studied here falls under this feedback category because it was connected to the GitHub Classroom autograding system: every pushed commit—which can be considered a prospective submission—launched a suite of unit tests and reported the results of those tests, as well as assigning a score. Available though perhaps less influential was the instructor's individual feedback while "making the rounds" while each lab was in progress. Thus, the results reported here may vary from results in courses where feedback on an assignment does not become available until after the due date.

3 Methods

In order to determine whether it was more beneficial for students to have a late penalty or an early incentive, we created the following four late policies:

1. No penalty for late submissions
2. Early incentive (one extra credit point awarded per day early the lab was submitted, up to three points max)
3. Late penalty (25% off within 24 hours of the deadline, 50% off for 24-48 hours late, 75% off for 48-72 hours late, and zero credit after 72 hours)
4. Combined early incentive and a late penalty

To ensure grading consistency across sections, every student was randomly assigned two labs per late policy, for a total of eight labs completed over the course of the semester. Extensions under the late penalty were granted if requested with at least 24 hours advance notice, and an amnesty policy midway through the semester allowed students to resubmit up to two of the first five labs, due to confusion regarding a new autograder feature we implemented.

Under IRB approval, we administered a Qualtrics survey (Fig. 1) to gather feedback and rankings for each of the late policies from students who volunteered to let us use their anonymous data. In total, 44 students responded to the survey and 31 gave us permission to use their data.

4 Results

As part of our qualitative evaluation, we asked students to *Please rank the four CMSI 186 late policies in order of your favorite (1) to least favorite (4).* As shown in Table 1, students liked the early incentive the most and the late penalty the least. Interestingly, when we asked a slightly different question, *Please rank the four CMSI 186 late policies in order of which ones you believe **best facilitate learning***, we found that although early incentive was still rated highest and the late penalty lowest, the average values had shifted closer together, and no policy was rated the same as the combined early incentive and late penalty. Students also commented:

- *I think that learning at your own pace is good, but also understand that a no policy can lead to **procrastination** and lack of lack of spacing out all the learning.*
- *I fell into this trap too but with the no policy something would happen where the lab would be **put off or postponed** but since there was no late policy that means the lab would be put off for weeks to the point where you would have to complete two even three labs at the same time.*
- *Early incentive gives me a goal to work toward in getting things done. Having no policy, at the very least, takes some of the time pressure off and enables me to make sure everything is done well.*
- *Turning labs in late always stresses me out, but during a week full of other exams, it's nice to know you can turn it in later.*
- *I think policies that reward good work ethic are more effective and fair than policies that punish poor work ethic. Some people aren't as organized as others or have differing conditions, and that should be okay. Of course, if it recurs, it should be addressed nonetheless. For that reason, having no policy is probably the worst, since although no one has an advantage*

Loyola Marymount University

Greetings programmers! Thank you for participating in our survey. We are evaluating the impact of different assignment submission policies on learning and assignment completion.

Your input will help shape the future of assignment policies at LMU and beyond!

Responses are anonymous and will in no way affect your grade in CMSI 186.

Is it okay to include your responses in our research and possible resulting publications?

Loyola Marymount University Informed Consent Form

TITLE: The Impact of Late Policies on Student Submission Behavior

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PURPOSE: To better understand the impact of late policies on student submission behavior. Different professors implement various late policies, ranging from strictly enforcing deadlines to flexibly allowing submissions through the end of the course. The purpose of this study is to determine whether there are certain policies that lead students to submit assignments early, potentially resulting in higher grades.

Figure 1: Screenshot of the Qualtrics survey we gave to students during the last week of class.

or disadvantage in terms of grades, not developing/improving a work ethic will be ultimately hurtful to the student in the long run.

- ***If I'm being totally honest I don't think "no policy" is the way to go 100% of the time. If it was I would always be behind and turning work in weeks late.*** *BUT... having the option a few times was HUGE. Between life stuff, other classes, etc there are times where it's so nice to have some latitude in your schedule. Feel like for a class like this (ie constant labs/coursework that needs to be turned in throughout the year) the happy medium would be to let students pick 2-3 times to use the "no policy" option (but then in general still make ppl stick to a schedule so they don't fall woefully behind).*

For the quantitative evaluation, we measured the average lab grade, as well as the average number of days the labs were submitted before or after the deadline, for each of the four late policies (see Tables 2 and 3). Even though students preferred the early incentive without a late penalty, the evidence from these two metrics shows that, on average, **labs had higher grades and were**

Late policy	Favorite	Best for Learning
No policy	2.03	2.39
Early incentive	**1.39**	**1.74**
Late penalty	3.81	3.48
Early incentive + late penalty	2.77	2.39

Table 1: Average rankings, from (1) best to (4) worst, for each of the late policies, for least/most favorite and best/worst for facilitating learning.

submitted earlier with the *combined* early incentive and late penalty. This is aligned with students' comments where they realized that although no late penalty is less stressful, it can result in procrastination and putting work off for weeks until it becomes too late to ever catch up.

Late policy	Mean Grade	Mean Grade (no 0 or extensions)
No policy	94.2%	97.4%
Early incentive	96.6%	99.6%
Late penalty	97.1%	99.3%
Early incentive + late penalty	**99.5%**	**101.3%**

Table 2: Average lab grades for each of the late policies, and average grades with outliers omitted (i.e., labs with a grade of zero or that were graded late with an extension).

Late policy	Mean Days Early (-) or Late (+)
No policy	+2.43
Early incentive	+4.71
Late penalty	+0.44
Early incentive + late penalty	**-1.45**

Table 3: The average number of days labs were submitted early (-) or late (+), for each late policy.

5 Discussion

Submission of assignments requires students to be motivated enough to work through them, whether they are motivated by genuine interest, the belief it will serve themselves or their goals, or by anticipated positive or negative consequences. Deci et al. apply the self-determination theory to education. They describe how autonomy, relatedness, and competence are required for the "central features of optimal learning [which] are conceptual understanding and the flexible use of knowledge."[22] Autonomy is emphasized as essential for intrinsic motivation or internalized sense of the task being worthwhile whereas relatedness and competence play supporting roles. There are several factors beyond the late policy that will influence feelings of autonomy and interest including the material itself, access to help and resources, classroom dynamics, etc. The late policy is of particular importance as it embodies power dynamics between teacher and student, and shapes the extent to which students are able to choose how to manage their own time. Late policies are a cornerstone of the learning environment. If leveraged effectively they can be empowering and foster accountability to self and community. Standard policies applied without critical awareness of these dynamics may instead demotivate and discourage.

Our study offers insight into the impact of points-based early incentives and late penalties. We suggest that late policies be determined based on careful consideration of course goals and the instructor's values. Over the course of a program, students will benefit from exposure to a variety of both.

Without time and resource constraints, instructors may naturally collaborate and engage with students as individuals, tailoring assignments and timelines to their individual interests, priorities, and contexts. In order to scale a learning environment to accommodate tens or hundreds of students, more general protocols are needed to keep track of progress through learning outcomes. The space between scale and individualization of education is ripe for creative solutions.

6 Conclusion

In this paper, we have reported on the effect of different late policies on student outcomes and attitudes for a computer programming laboratory course. Within the same course offering, instructor, and content, students were given different combinations of early submission incentive and late submission disincentive for certain assignments. The collected results suggest that having an incentive but no disincentive was the most favored policy but having *both* an incentive and disincentive produced the best performance. The work builds on prior evidence that procrastination and late submissions have a negative impact on student well-being and outcomes but situates this (a) within a computer science context, specifically computer programming; (b) within a *single* course offering to minimize the impact of other variables; and (c) alongside incentives as well, in order to encourage *early* submission. The study also examines student perceptions toward the policy variations alongside their final measurable outcomes.

The study has both anticipated and unanticipated limitations: first, the number of sections and overall number of students who participated in the study are relatively small given the size of our computer science program in relation to others. Second, due to the course's place in the curriculum, most of the students were in the second half of their first years in college and thus very early in their trajectories as computer scientists and software developers. An equivalent study with upper-division students may reveal whether submission habits change with time, experience, and maturity. Finally, the study was impacted by the coronavirus pandemic by forcing the course online when it would have otherwise been studied in-person. Although we do not believe that the online/in-person factor would change the overall conclusion, for completeness it may be worthwhile to conduct the same study with a different modality (when feasible) to determine the *degree* to which outcomes may vary.

Students, courses, instructors, modality, and many other factors make every course offering and experience unique, so we may never be able to make a universal statement on how late policies affect student perceptions and outcomes. As such, there will always be room to include more elements, variables, or parameters in future studies along these lines. However, these particular follow-ups may have immediate value: student-selected vs. preassigned policy-to-assignment mapping; upper-division courses; and online vs. in-person modalities. Post-degree performance may also be of interest, if challenging to set up: how do early incentive and late disincentive factor into outcomes *after* graduation? As with many examinations of *student* outcomes, these studies' ultimate value may be as a predictor for how corresponding factors affect eventual performance as software developers, researchers, or other professionals later in life.

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